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The Language of Character Strengths: Predicting Morally Valued Traits on Social Media

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Abstract

Objective. Social media is increasingly being used to study psychological constructs. This study is the first to use Twitter language to investigate the 24 Values in Action Inventory (VIA) of Character Strengths, which have been shown to predict important life domains such as well-being. **Method**. We use both a top-down closed-vocabulary (Linguistic Inquiry and Word Count) and a data-driven open-vocabulary (Differential Language Analysis) approach to analyze 3,937,768 tweets from 4,423 participants (64.3% female), who answered a 240-item survey on character strengths. **Results.** We present the language profiles of (1) a global positivity factor accounting for 36% of the variances in the strengths, and (2) each of the 24 individual strengths, for which we find largely face-valid language associations. Machine learning models trained on language data to predict character strengths reach out-of-sample prediction accuracies comparable to previous work on personality (r_{median} = .28, ranging from .13 to .51). **Conclusions**. The findings suggest that Twitter can be used to characterize and predict character strengths. This technique could be used to measure the character strengths of large populations unobtrusively and cost-effectively.

Keywords: character strengths, language analysis, social media, Values in Action survey, well-being

The Language of Character Strengths: Predicting Morally Valued Traits on Social Media

Studies have shown that social media (e.g., Facebook and Twitter) provides substantial quantities of autobiographical language and linguistic behavior that are related to users' psychological characteristics (e.g., Eichstaedt et al., 2015; Kosinski, Stillwell, & Graepel, 2013). Twitter averages about 330 million monthly active users (Statista, 2018), with about 500 million daily tweets (Aslam, 2018). People use social media to discuss thoughts, opinions, feelings, and the activities and relationships that constitute their everyday lives (Schwartz et al., 2013a). For these reasons, social media platforms are rapidly gaining recognition as research tools for the social sciences (Ruths & Pfeffer, 2014). Among studies which show that social media can be used to generate insights and predictions concerning psychological constructs, personality traits have received considerable attention in recent years (e.g., Dewey, 2015; Park et al., 2015; Qiu, Lin, Ramsay, & Yang, 2012; Schwartz et al., 2013c; Youyou, Kosinski, & Stillwell, 2015).

Research using social media to study psychological traits has so far focused primarily on the Five-Factor Model of personality (FFM or the Big 5, see Azucar, Marengo, & Settanni, 2018, for an overview). For example, results reveal that extraverts are more likely to mention social words (e.g., *party*, Schwartz et al., 2013c), are more prone to use social media (e.g., Blackwell, Leaman, Tramposch, Osborne, & Liss, 2017), connect with more friends on social media (Kosinski, Bachrach, Kohli, Stillwell, & Graepel, 2014), and tend to have more Twitter followers (Quercia, Kosinski, Stillwell, & Crowcroft, 2011) than introverts. Individuals who are high in openness are more likely to use words related to creativity and imagination (e.g., *art* and *dream*, Schwartz et al., 2013c), tend to have larger networks (Quercia, Lambiotte, Stillwell, Kosinski, & Crowcroft, 2012), express more "likes", have more status updates, and engage in more group activities on social media (Bachrach, Kosinski, Graepel, Kohli, & Stillwell, 2012) than individuals low in the trait. Individuals with high neuroticism use more negative words in their posts (Schwartz et al., 2013c), are more prone to use social media as a safe place for self-presentation (Seidman, 2013), have fewer Twitter followers (Quercia et al., 2011), and are more likely to be addicted to the Internet (Blackwell et al., 2017) than low-neuroticism individuals. Agreeable individuals are relatively likely to express positive emotions in their posts (Schwartz et al., 2013c) and to display positive emotions in their profile pictures (Liu, Preotiuc-Pietro, Samani, Moghaddam, & Ungar, 2016). Individuals with high conscientiousness appear to be cautious in their online self-presentation; they tend to post fewer pictures (Amichai-Hamburger & Vinitzky, 2010), join fewer groups, and use "likes" less frequently on social media (Kosinski et al., 2014) than low-conscientiousness individuals. Their tweets tend to be more clicked, replied and retweeted (Quercia et al., 2011). In addition to looking at links between social media behavior and the Big 5, recent studies also have explored how social media can be used as a tool to predict the Big 5. For example, Park et al. (2015) provide evidence that language-based assessments (Facebook language) agree with self-reports and informant reports of personality. Surprisingly, Facebook Likes are more accurate than peer-ratings of personality, i.e., those made by participants' Facebook friends (Youyou et al 2015). Another study has shown that Twitter profiles (e.g., followers, following, and listed counts) can accurately predict users' Big 5 traits with a root-mean-squared error below .88 on a 1 to 5 scale (Quercia et al., 2011).

Despite growing interest in research on social media and the Big 5, much less is known about other models of personality. We focus on the morally valued traits, which have been mostly neglected within personality psychology for a long time. This neglect can be dated to the time of Gordon Allport (1897-1967), who claimed in the 1930s that character is merely "personality evaluated, and personality is character devalued" (Allport 1937, p. 52). Peterson and Seligman (2004) can be seen as a milestone in reviving interest in morally valued traits as a distinct topic of research by proposing the Values-in-Action (VIA) classification of character strengths. Character strengths are a family of morally valued traits that have emerged across cultures and throughout history as important for contributing to a fulfilling life (Peterson & Seligman, 2004). Character strengths are associated with the good life, or positive life outcomes: studies have shown links between character strengths and positive emotions (e.g., Güsewell, & Ruch, 2012), academic achievement (e.g., Weber & Ruch, 2012), healthy behaviors (e.g, Proyer, Gander, Wellenzohn, & Ruch, 2013), mindfulness (Pang & Ruch, 2019a), life satisfaction and multi-dimensional well-being (Wagner, Gander, Proyer, & Ruch, 2019), and orientation to happiness (e.g., Buschor, Proyer, & Ruch, 2013; Peterson, Ruch, Beermann, Park, & Seligman, 2007; Ruch, Huber, Beermann, & Proyer, 2007). Beyond that, character strength interventions have been shown to improve well-being and reduce depressive symptoms and stress (e.g., Gander, Proyer, Ruch, & Wyss, 2013; Proctor et al., 2011; Proyer, Gander, Wellenzohn, & Ruch, 2015; Proyer, Ruch, & Buschor, 2013, Pang & Ruch, 2019b). Supplemental Table S1 outlines the framework of the VIA classification, including an overview of the 24 character strengths.

Although there are both conceptual and empirical overlaps between character strengths and the Big 5, such as agreeableness with kindness and conscientiousness with perseverance (Macdonald et al. 2008; Peterson & Seligman, 2004), recent studies also have identified substantial distinctiveness between the two models of personality traits. Park and Peterson (2006) found correlations between VIA strengths and the FFM variables no greater than .50 in a group of adolescents. Notfle, Schnitker, and Robins (2011) revealed that the percentage of variance in character strengths explained by the Big 5 domains ranges from 14% (spirituality) to 46% (persistence) with a mean percentage of 33% across the 24 strengths. McGrath, Hall-Simmonds, and Goldberg (2017) demonstrated that spirituality is the least effectively represented by the FFM facet measures (less than 20% of explained variance) and in only three cases (creativity, forgiveness, and perseverance) does their best single predictor account for as much as half the variance in the strength scale. In addition to the direct relationship between character strengths and the Big 5, there is evidence for the incremental validity of the former over the latter from predicting self-reports of well-being (Noftle et al., 2011; Johnsen, 2014), helping behaviors (Lefevor & Fowers, 2016), and other behavioral criteria (e.g., friendliness and erudition; McGrath et al., 2017). Therefore, looking at the language of the VIA character strengths on social media in addition to the current findings for the Big 5 would allow us to capture more nuanced individual differences and provide a richer understanding of character strengths.

The 24 strength scales are positively intercorrelated, raising the question of an underlying global factor. For example, Ruch et al. (2010) discovered comparable intercorrelations among the scales in both self- (median r = .36) and peer-reports (median r =.38), and McGrath (2014) reported a mean intercorrelation of derived factors of .39. The first unrotated principal component alone typically explains about 40% of the variance (McGrath, 2015). This is why Ng et al. (2017), when identifying the factor structure of the scales, chose to apply a bi-factor model with a separate global positivity factor capturing dispositional tendencies toward well-being (rather than a methodological artifact).

Thus, we expect that substantial overlap among the language correlates of the 24 character strengths would make it difficult to determine patterns distinctive to each of the 24 strengths. For this reason, we examine the language insights of this global positivity factor separately from the language insights of the 24 individual strengths. We postulate that (1) the global positivity factor (GPF), namely the first unrotated principle factor (FUPC), will capture increased use of positivity-related words associated with higher scores on character strengths overall (Ng et al., 2017); and (2) each character strength will yield specific language insights when the other 23 strengths, as well as age and gender, are controlled for[1]. Our goal is to identify a unique linguistic profile for each of the 24 character strengths and to provide insights regarding the cognitive, affective, and behavioral concomitants of these morally valued traits.

The Present Study

The primary goal of this study is to use Twitter language to illuminate the expression of the 24 character strengths. We use both a dictionary-based approach (Linguistic Inquiry and Word Count [LIWC] 2015; Pennebaker, Booth, Boyd, & Francis, 2015) and a data-driven open-vocabulary method (Differential Language Analysis [DLA], Schwartz et al., 2013b). We hypothesize that significantly associated words and topics will yield nuanced linguistic cues for the GPF and each character strength. A supplementary goal of the present study is to predict user-level character strengths from Twitter language models, which eventually could serve as a cost-effective and scalable way to assess character strengths. A prediction tool will be useful because the reliable and valid measures of the character strengths, including the original 240-item (Peterson, Park, & Seligman, 2005) and the revised 120-item measures (McGrath, 2017), are quite long and mostly self-report measures.

Materials and Methods

Participants and Procedure

From an initial pool of 17,636 self-selected volunteers, 4,423 participants ultimately were analyzed in the current study (see Supplemental Figure S1 for the participant flow and the selection criteria[2]). The initial self-selected volunteers registered on the Authentic

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[1] Here we did not partial out the GPF but used the other 23 strengths because we aimed to make the statistical control more similar across strengths, especially for strengths that loaded highly on the GPF and those who did not. We also conducted the analyses by gender. However, the results between males and females were very similar and no different patterns occurred in our current analysis.

[2] Selection criteria were: (1) time stamp from January 2014 to March 2018 (removed n = 303); (2) when the VIA was taken multiple times, only the most recent response with a distinct Twitter handle was used (removed n = 968); (3) English indicated as primary language (removed n = 4,529); (4) participants must have item-level responses (removed n = 151) and also give responses not suggestive of premature completion (removed n = 285); (5) Of those 11,400 participants, 7,987

Happiness site (www.authentichappiness.sas.upenn.edu) hosted by the Positive Psychology Centre at the University of Pennsylvania and completed the Values in Action Inventory of Strengths using their personal devices. Upon registration, participants had the option to provide their Twitter handle for research purposes, after reading and agreeing to an informed consent statement.

The final sample consisted of 4,423 participants (64.3% female) ranging from 18 to 65 years in age (M = 32.3, SD = 12.5). The participants were well-educated: 0.9% of them had less than a high school degree (n = 39); 38.9% of them were high school graduates or some college course work (n = 1,722); and 60.2% of them had a bachelor's degree or more (n = 2,262). The sample covered a variety of occupations, including students (29.3%), professionals (13.2%), clerks (8.2%), chief executives (6.1%), manual laborers (5.3%), artists and actors (3.8%), homemakers (0.4%), and people who were retired/unemployed/invalid (3.8%). Around one-third of them did not report their occupations (29.8%). The majority of the participants came from the United States (n = 2,783; 62.9%). The rest of the participants came from the United Kingdom (n = 383; 8.7%), Canada (n = 280; 6.3%), Australia (n = 256; 5.8%) and other countries (< 2%).

We used the Twitter Application Programming Interface (API) to query up to the most recent 3,200 tweets from each volunteer[3]. This resulted in 3,937,768 status updates. Respondents were not paid for participating but were provided with an automatically generated summary of their character strengths. All procedures were approved by the University of Pennsylvania Institutional Review Board (protocol #816091).

participants provided a valid Twitter handle. We then used an open-source python package, the Differential Language Analysis Toolkit (DLATK; Schwartz, et al., 2017) to filter the spam, non-English and duplicated tweets, and thus retained 7057 Twitter users with sufficient Twitter language. We further restricted our analysis to (6) adults younger than 65; (7) who did not give Twitter handles of celebrities (by removing users who have more than 5000 followers); (8) and who had at least 1,000 words across tweets per user after filtering for spam and duplicates.

[3] This is a limitation imposed by the Twitter API. This method can only return up to 3,200 of a user's most recent Tweets. See the following link for more details: https://developer.twitter.com/en/docs/tweets/timelines/api-reference/get-statuses-user_timeline.html.

Character Strengths Measure

The character strengths of the participants were measured by the Values in Action Inventory of Strengths (VIA-IS; Peterson et al., 2005). It is a self-report questionnaire consisting of 240 items, which measures the 24 character strengths of the VIA classification (10 items for each). A sample item is "I never quit a task before it is done (*perseverance*)." The reliability of the 24 scales was adequate to high with Cronbach's alpha ranging from .74 (*prudence*/*honesty*) to .90 (*spirituality*) with a median value of .80 (see Table 1).

Outcome Variables

Two sets of outcome variables were defined in the present study. First, the first unrotated principal component (FUPC) of the 24 character strengths represented the global positivity factor (GPF). Second, to derive distinctive linguistic insights for each character strength, we controlled for the influence of the other 23 character strengths by using the residual of the character strength from a regression analysis with the specific character strength as a criterion and the remaining others as predictors. As shown in previous studies, age and gender impacted language use (e.g., Kern et al., 2014, Schwartz et al., 2013b), and thus we controlled for these demographics in all analyses by including them as covariates in our regression models.

Linguistic Analyses

Closed-vocabulary. First, using our Python-based open-source code base, the Differential Language Analysis Toolkit (DLATK; Schwartz, et al., 2017), we extracted 73 dictionaries ("categories") provided by LIWC2015 (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Dictionaries included psychological (e.g., positive emotion), life domain (e.g., family and home), and syntactic categories (e.g., pronouns). We also extracted the relative frequency of each dictionary (i.e., the total number of time a word written by the user matches a word in a given dictionary, divided by the user's total number of words). We explored the most positive and negative correlations of the relative frequency of the LIWC categories with the GPF score. In addition, we explored the most positively correlated LIWC categories of each character strength. Our reason for using LIWC was to examine the correlates of the 24 strengths in a variety of domains. Moreover, using LIWC categories had the advantage that results found here could be more easily compared with the existing literature as LIWC has been widely used in psychology research.

Open-vocabulary. Second, again using DLATK, we performed DLA (Schwartz et al., 2013b) to identify the most distinguishing language features for our outcomes. We split ("tokenized") the tweets into words, punctuation, emoticons (tokenization; Potts, 2011), and we extracted phrases consisting of two or three consecutive words (called 1-3 grams in the present study, for details of the methodology see Kern et al., 2016, Schwartz et al., 2013a, Schwartz et al., 2013b). We kept only those 2- and 3-word phrases with high pointwise mutual information (PMI = 5; Church & Hanks, 1990; Lin, 1998), a ratio of the probability of observing the phrase to the probability of observing the constituent words independently. This procedure yielded 11,901 language variables for each user, encoding the use of tokens and phrases. We correlated the global positivity factor and the 24 residuals of the character strengths against all the one- to three-word phrases we extracted from their tweets and shortlisted the most strongly associated words/phrases. As this is an exploratory technique, we utilized the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) to correct for multiple comparisons and control the false discovery rate (FDR) over correlation tests for 11,901 language features. We selected only Benjamini-Hochberg significant 1-3 grams and topics.

Third, we used a set of 2,000 previously created topics (Schwarz et al., 2013a), clusters of semantically-related words derived through Latent Dirichlet Allocation (LDA), a clustering algorithm akin to factor analysis but appropriate for the statistical distributions of words (Blei, Ng, & Jordan, 2003). For each user, we extracted the relative use of these 2,000 topics.

Predictive Model Based on Language

We trained and evaluated a ridge regression model (Hoerl & Kennard, 1970) to predict the users' 24 character strengths (the original scale scores) using the 2,000 topics as predictors, using age and gender as covariates. The statistical model could be summarized as follows:

$$\mathrm{Y_{i,t}} = \mathrm{C_t} + \gamma_{\mathrm{t,0}}\mathrm{Age} + \gamma_{\mathrm{t,1}}\mathrm{Gender} + \sum_{\mathrm{p=1}}^{2000} \beta_{\mathrm{t,p}}\mathrm{X_{p,i}}$$

$\mathrm{Y_{i,t}}$ refered to the scores of each users' character strengths with i representing the user index (ranges from 1 to 4,423) and t representing the strength index (ranges from 1 to 24). $\mathrm{X_{p,i}}$ refered to the probability of a subject's use of each LDA topic with p representing the topic index (from 1 to 2,000) and $\mathrm{C_t}$ refered to the intercept for strength t. Ridge regression models were trained and evaluated using 10-fold cross-validation (CV). In this procedure, the 4,423 users were split into 10 groups. For each group G, a ridge regression model was trained on the other 9 groups and then used to predict scores for G. For each group we tested an array of ridge regularization parameters and reported the predictions corresponding to the model with the best performance on G. In this way we ultimately obtained out-of-sample predictions for all 4,423 users. The predictions were out-of-sample in the sense that the model was trained only on the training set, although the ridge parameter ultimately was tuned on the prediction set. The accuracy of the predictive model was assessed by the Pearson's *r* coefficients (correlation between the user's character strengths score and their out-of-sample predicted values) and as the mean absolute error (MAE, the absolute difference between the user's character strengths score and their predicted values, in units of the 1-5 original scale). As a baseline, we used age and gender of the users to predict each character strength. After conducting the Fisher's (1915) z transformation, a t-test was used to compare the two correlation coefficients.

Results

For preliminary analyses, we computed descriptive statistics for all 24 character strengths, the loadings of each character strength on the first unrotated principal component and the Pearson's *r* correlation of each character strength with the other 23 strengths partialled out. Additionally, we included the eigenvalues of the first seven components as well as their explained variance. The results are displayed in Table 1.

Insert Table 1 around here

The Language of the Global Positivity Factor

As shown in Table 1, the GPF explained 35.7% of the variance in the our sample. Almost all 24 character strengths loaded well on the FUPC with loadings ranging from .32 (*modesty*) to .74 (*gratitude*), and most loadings were close to the median of .61. Both closed (LIWC) and open (DLA) vocabulary analyses revealed that the strongest positive correlations with the GPF score were words suggestive of social affiliation, positive emotions, and first person plural pronouns (e.g., *love* and *our,* β = .13 to.15, $p < .001$). The strongest negative language correlations with the GPF score were common adverbs, negative emotions, and words related to differentiation and tentativeness (e.g., *also*, *bad*, *but*, and *would,* β =-.17 to -.16, $p < .001$). Table 2 shows the top 10 most positively and negatively correlated LIWC categories (as well as the most frequent words within these categories). In addition, a high GPF score was associated with words that indicated a positive life attitude, such as *blessed*, *patience*, *moments*, and *passion,* whereas a low GPF score associated with hedging words such as *actually*, *probably*, *supposed*, and *apparently*.

Insert Table 2 around here

In a similar pattern, the LDA topics that correlated most positively with the GPF score revolved around social connections (e.g., *family* and *friends,* β = .17), religiousness (e.g., *god* and *lord,* β = .16), a sense of gratitude (e.g., *blessed* and *thankful,* β = .16), faith and optimism (*strengths* and *overcome,* β = .15), an attitude of living in the present (*life* and *cherish,* β = .14), and positive emotions (e.g., *happiness* and *joy,* β = .14). By contrast, the topics that correlated most negatively with GPF revolved around negative emotions (*bad,* β = .16), negations (e.g., *wasn't* and *isn't,* β = .16), a more past-oriented cognitive style (e.g., *thought*, *forgot*, and *realized,* β = .14) and hedging (e.g., *supposed* and *apparently,* β = .14). Figure 1 shows the 100 most distinctive words and phrases as well as the LDA topics for the GPF.

Insert Figure 1 around here

The Language of the 24 Character Strengths

As discussed above, the 24 character strengths substantially co-vary. To derive the distinctive language insights for each specific character strength, we partialled out the influence of the other 23 character strengths, using the residual as the outcome variable in our linguistic analysis. The residual of the character strengths correlated significantly with the scale scores of the strengths, with median correlation of r = .68 (ranging from .56 for zest to .79 for spirituality, see Table 1). The results of the linguistic analysis for each character strengths are summarized in Figure 2. Additionally, to give a better sense of the context in which the most correlated words/phrases/topics appeared, we present random selections of tweets featuring these items (see Supplemental Table S2).

As shown in Figure 2, the DLA results of *creativity* showed significant associations with words indicative of people who work in creative professions such as technology (e.g., *Facebook* and *technology*) and creative work (e.g., *creative*, *design* and *artist*). The top three LDA topics also indicated creative professions (*Facebook* and *hacked*; *computer* and *program*; and *art*, *design*, and *museum*).

The language of *curiosity* suggested an interest in exploring new experiences. The top-correlated LIWC categories were space and relativity (e.g., *in*, *on* and *at;* indicators of being in new/different places), leisure (e.g., *twitter*, *fun*, and *play;* indicators of exploring) and ingestion (e.g., *eat*, *water*, and *sweet;* indicators of trying new food/drinks). Similarly, the most correlated words were related to space and relativity (e.g., *on*); travelling or other cultures (e.g., *France* and *Korean*); and leisure and activities (e.g., *festival* and *park*). The top-correlated topics also which also referenced travel destinations (*Paris* and *London*), leisure (*lake* and *boat*), and activities (*festival* and *film*).

The most representative words of *judgment/critical thinking* referenced thinking (e.g., *know* and *think*), consideration (e.g., *bad* and *appropriate*), and differentiation (e.g., *not* and *but*), which were essential for thinking things through (e.g., *stop* and *bad*) and examining from all sides (e.g., *not* and *don't*). The highly-correlated topics likewise revolved around opinions, objective statements, and judgmental comments.

Love of learning was associated with syntactic categories that mark more complex language use (e.g., use of articles, *the* and *a*), topics concerning school (e.g., *school, books*, and *read*), insights (e.g., *know* and *think*), and inquisitive language (e.g., *why* and *how*). This is consistent with the top-correlated topics like opinions, books and reading, as well as political discussions.

The language of *perspective* was in line with a view towards life that emphasizes what matters most. Top-related words and phrases included *important*, *makes me so*, *so much*, *life*, and *statements*, similar to the only cluster of topics significantly associated with perspective (e.g., *important*, *life*, *things*, and *realize*).

Bravery seemed to be associated with references to aggression (e.g., *hate*, *kill*, and *fuck*), masculinity (e.g., *he, father,* and *man*), freedom (e.g., *fight*), rights (e.g., *rights*, *racist* and *woman*), and politics (e.g., *vote* and *political*). The top-related topics included swear words, freedom and rights, and politics.

The most representative words of *perseverance* revolved around work (e.g., *work*), school (e.g., *graduation* and *congrats*), achievement (e.g., *best* and *first*), and suggested a future-oriented mindset (e.g., *when* and *new*), in line with individuals who tended to complete the tasks they set out to accomplish. The highly-correlated topics likewise revolved around study (e.g., *English* and *history*), graduation (e.g., *congrats* and *graduation*) and achievement (e.g., *grades* and *final*).

The most representative words of individuals high in the *honest /authentic strength* included self-reference (e.g., *I* and *my*) and revelations of personal distress (e.g., *sleep* and *head*) as well as potentially reduced self-control, indicated by greater use of swear words (e.g., *fuck* and *hell*). These also appeared similarly in the top-related topics, such as *sleep*, *gotta* and *tired*.

The most representative words of *zest* showed positive emotions (e.g., *love* and *good*), excitement (e.g., *great*, *passion*, and *forward*), and energetic pursuit of life and work (e.g., *work* and *school*). Individuals high in this strength also mentioned more social connections (e.g., *we* and *our*) and words related to achievement (e.g., *best* and *work*). The highly-correlated topics likewise revolved around weekend (e.g., *weekend* and *holiday*), positive emotions (e.g., *great* and *awesome*), and future-orientation (e.g., *forward* and *hope*).

The words most associated with *love* referred to relationships (e.g., *my boyfriend* and *he loves*) and gratitude (e.g., *thank* and *thanks so much*). Individuals high in this trait also seemed to value close relationships with others (e.g., *wish I could* and *guardian [angels]*, Supplemental Table S2), and care about sharing (e.g., *care about* and *recourses*).

Individuals high in *kindness* expressed support of others (*well*, *hugs* and sorry *to hear*), were interested or engaged in charity (e.g., *raise [money]*, Supplemental Table S2), and appeared to value close relationships (e.g., *best friends* and *washing [for others]*, Supplemental Table S2).

The most representative words of individuals high in *social intelligence* tended to be informal (e.g., *u, :)*, and *lol*), with positive emotional content (e.g., *love* and *good*) and social language (e.g., *catch up* and *conversation*). The top-related LDA topics showed similar patterns, revolving around social events (e.g., *night*, *town*, and *carnival*) and positive emotions (e.g., *love*, *hugs* and *xoxo*).

The most representative words of *teamwork* reflected achievement. The top-correlated LIWC categories were reward (e.g., *good* and *great,* $\beta = .04$, $p < .05$), achievement (e.g., *best* and *first,* $\beta = .04$, $p < .05$), and religion (e.g., *god* and *holy,* $\beta = .04$, $p < .05$). In addition, words of support and encouragement (e.g., *c'mon [come on]* and *congrats*), future orientation (e.g., *future*), family (e.g., *father*), and work life (e.g., *office*) were highly correlated with the character strength of teamwork. However, we found no significant correlations between LDA topics and *teamwork*.

Fairness was associated with words related to self-reference (e.g., *I* and *my*) and more frequent negations (e.g., *but*, *no,* and *don't*). The highly-correlated topics likewise revolved around common adverbs (e.g., *honestly* and *anymore*), negations (e.g., *don't* and *won't*), and common verbs (e.g., *talking* and *suppose*).

Leadership as a character strength was associated with the language of affiliation (e.g., *we* and *our*) and activities and events commonly engaged in by leaders (e.g., *challenging*, *workshops*, *presentation*, and *manage*). The top-correlated topics suggested further common behaviors of leaders, such as giving charity (e.g., *donate* and *raise*), attending events (e.g., *event* and *ticket*), and acting future-oriented (e.g., *hope* and *forward*).

The most representative words of *forgiveness* were indicative of close relationships (e.g., *marriage*) and the process of apology (e.g., *believed* and *appeal*).

Similarly, *modesty* showed associations with *races*, which in this context appeared to be running competitions (see Supplemental Table S2 for more details). In addition, the words related to *modesty* also involved proclamations of effort (e.g., *forward to*, *hustle*, and *catch up*).

Prudence was associated with adverbs such as *simultaneously*, *also*, *recently* and *apparently*. Individuals high in *prudence* seemed to talk about clicking links (*clicked*) and also tended to use LDA topics previously shown to be characteristic of introverts (Schwartz et al., 2013c), such as suspenseful movies (e.g., *sherlock and inception*), anime (e.g., *anime* and *manga*), and common adverbs and verbs (e.g., *apparently* and *found*).

The most representative words associated with *self-regulation* was suggestive of rigorous, healthy lifestyle and self-discipline (e.g., *life*, *health, gym*, *workouts*, *diet*, and *weights*). The highly-correlated topics likewise included workouts (e.g., *gym* and *exercise*), diet (e.g., *eating* and *drinking*), and losing weight (e.g., *lose* and *pounds*).

The most representative words of *appreciation of beauty and excellence* was suggestive of individuals who expressed themselves (e.g., *I* and *my*; indicators of expressing oneself) emotionally, liked to observe aesthetic work attentively (e.g., *see, look, art*, and *beautiful*; indicators of observing attentively), and expressed intensity (e.g., *fuck* and *hell;* to address the intensity). These patterns also were revealed in the top-correlated topics, which indicated emotional sensitivity (*tears* and *cry*), art (*song* and *music*), and positive emotions (*beautiful* and *wonderful*).

The most representative words of *gratitude* showed that individuals high in this strength were thankful (e.g., *so grateful for* and *blessed*) and experienced positive moods (e.g., *impressive* and *amazing*) in social contexts (e.g., *congrats* and *happy birthday to*). The most-correlated LIWC categories were male (e.g., *he* and *his*) and social processes (e.g., *you* and *love*); both indicated objects/subjects of gratefulness. The highly-correlated topics likewise included male references (e.g., *dad* and *boyfriend*), people (e.g., *baby* and *girl*), and social processes (e.g., *family* and *friends*).

Individuals high in *hope* were future-orientated (e.g., *a brand new*) and optimistic (e.g., *confident, id [I'd]*, and new *products*). The topics showed one significant result, namely abbreviation denoting one's mood (e.g., *na* and *sa* [concrete example: *<USER> when you're ready come and get it la na na*, see Supplemental Table S2 for more details]).

The language of *humor* showed that individuals high in this trait tended to talk about themselves frequently (e.g., *I* and *me*) and responded to jokes (e.g., *jokes* and *funnier*) and funny content (e.g., *toilet* and *dumb*). The highly-correlated topics likewise included funny content (e.g., *toilet, pee, smell* and *fart*) and responses to jokes (e.g., *hahaha* and *laughing*).

The language associated with *spirituality* was indicative of individuals who practice their religion actively (e.g., *god*, *church*, *praying,* and *lord*), positive emotions (e.g., *blessed*), and were socially connected (e.g., *family* and *mum*). The highly-correlated topics likewise revolved around religious themes such as god (*god* and *prayers*), gratitude (e.g., *blessed* and *grateful*), and religious events (e.g., *service* and *church*).

Predicting Character Strengths with Language

As shown in Table 3, the predictive models performed comparably to other models predicting constructs like personality from behaviors[4], with models for *love of learning* and

[4] It is rare to have an *r* over 0.3 for such models; the out-of-sample correlation between the personality score predicted by the model (or the LDA topic) and the questionnaire-based personality assessments usually fall below .30 to .40 (Golbeck, Robles, Edmondson, & Turner, 2011; Park et al., 2015; Schwartz et al., 2013c).

spirituality performing excellently (*r* reaching .51) and models for another six strengths (i.e., *zest*, *appreciation of beauty and excellence*, *gratitude*, *curiosity, hope and self-regulation*) performing relatively well (*r* greater than .30). The strengths that were easiest to predict from Twitter language had also higher relative frequency of 1-3 grams and topics (as indicated by the color of the word clouds and topic clouds). The reason behind the difference in prediction values might be that certain character strengths were more manifest on social media platform, while other strengths were more hidden. For example, love of learning indicates a certain degree of openness, which is linked to more social media activities (e.g., more “likes” and larger network) and also a tendency to post more content, whereas prudence indicates a degree of introversion which may correlate with less social media use.

Insert Table 3 around here

Discussion

The present study investigates language use associated with the 24 VIA character strengths, extending previous work on the language profiles of the Big 5 to morally valued traits (Schwartz et al., 2013c). We demonstrate that each of the 24 character strengths and a global positivity factor are associated with distinctive language profiles and can be accurately predicted by social media language with fair accuracy.

The present study expands existing knowledge on the overlaps and distinctiveness of the Big 5 and the VIA character strengths. Consistent with what Peterson and Seligman (2004) point out, our results show that four out of the Big 5 traits have clear counterparts in the virtue domain (see Table 4). Comparing the results of Twitter language on the Big 5 (c.f. Schwartz et al., 2013c, Figure 6 and Figure S2) with our results reveals how the word clouds of the Big 5 differ or coincide the VIA character strengths. For instance, both extraversion and zest correlate with words related to time for socialization (e.g., *weekend*) and positive emotion (e.g., *great*), but the language of zest additionally shows indications of enthusiasm (e.g., *passion*). In a similar vein, both openness and appreciation of beauty are related to artistic work (e.g., *music*), yet the latter further emphasizes aesthetic value (e.g., *beautiful*). This constitutes evidence that the Big 5 and VIA character strengths are complementary measures, with analysis of the VIA strengths contributing to a more nuanced understanding of individual differences.

Insert Table 4 around here

The words/phrases that are most positively associated with the GPF suggest positive emotionality, which captures a number of character strengths (e.g., *beautiful*, *love*, *faith*), and language associated with emotional (e.g., *happy* and *passion*) and social well-being (*family* and *friend*) and accomplishment (e.g., *success*). This general pattern of results is largely consistent with previous computational linguistic analyses on religious affiliation (Yaden et al., 2017). We additionally observe language suggestive of mindfulness (i.e., focusing on the current moment, e.g., *moment* and *breaths*). This is consistent with previous studies on the association between character strengths and mindfulness (Pang & Ruch, 2019a) as well as life satisfaction (for an overview, see Bruna, Brabete, & Izquierdo, 2018). The linguistic cues in the present study provide support for the potential contribution and association of character strengths to both the hedonic (e.g., happiness or positive affect) and the eudemonic (e.g., a sense of meaning and purpose) aspects of well-being (Wagner et al., 2019). In the pattern of negative association, we observe a tendency towards more cognition and differentiation but not the use of swear words, which mark disagreeableness and cognitive dysregulation.

These observations raise the question of what exactly the GPF is. Is it a method artifact that reflects social desirability or an indicator of positivity? Given the high loadings of all character strengths on the GPF (median loading .61, and higher than .70 for gratitude, zest, leadership, hope, and perspective), and its associated language profile suggestive of positive emotionality and well-being, the GPF would suggest more of the latter (indicator of positivity) for the following reasons. First, gratitude, zest, hope, curiosity and love loaded strongly (i.e., ≥ .60) on the GPF, which happen to be the five strengths most robustly correlating with well-being across different samples (e.g., Buschor et al., 2013; Park, Peterson, & Seligman, 2004; Ruch et al., 2007; Ruch et al., 2010; Shimai et al., 2006). The higher the loadings of each strength on the GPF, the higher its correlation value with life satisfaction (rank-order correlation ranges .63 from to .81, computing correlations with Park et al., 2004, Table 3). Second, the overall level of virtuousness that has been ascribed to each character strength (gratitude [3.34], zest [2.72], love of learning [3.06], modesty [3.36]; Ruch & Proyer, 2015) does not seem to have a systematic impact on whether the character strength loads strongly (gratitude and zest) or weakly (love of learning and modesty) on the GPF. In sum, this suggests that the GPF may capture a sort of dispositional positivity – a trait-like "meta positivity" – that constitutes emotional well-being and emotional health rather than a methodological artifact. Nevertheless, it is possible that the GPF represents a prevalence of positivity-related words because no reversed items are available in the VIA-IS. This suggests that a "less fakable" balanced key version of the VIA-IS (e.g., McGrath, 2017) may be worth developing and that researchers should additionally try to measure character strengths through peer ratings (Ruch et al., 2011) or structured interview (Peterson & Seligman, 2004). The theoretical implications of a general positivity factor observed in psychometric studies and computational linguistic analyses is worthy of further discussion and research.

The language insights help to reveal the everyday lives of individuals who are high in each particular strength. For example, it is easy to imagine that a person who scores high in *love of learning* may love books, read a lot, be interested in history and have the drive to study – and the language results support this prototypical view. We still see *grateful* and *care* in the language of *love* despite the fact that the positive emotionality of the GPF was partialled out, suggesting that these language cues are indicative of *love* over and above the GPF language profile.

If the goal is to have the full picture of each individual strength (i.e., rather than the distinctiveness of each strength), then an analysis of individual VIA-IS scales should be undertaken. As noted, this leads to largely overlapping word clouds given the large shared overlapping variance in the GPF. We avoid this problem in the present study and provide a technique to address this challenge[5]. For studies interested in what differentiates strengths, we recommend using this meta-positivity GPF as a control variable and examining correlates of each strength above and beyond GPF.

Our prediction results are comparable to previous work on personality prediction and suggest that language-based assessment of character strengths may one day serve as a cost-effective and scalable alternate measurement system. Social media language (e.g. from Twitter) constitutes a new medium for assessing individual differences which allows insights into other life domains such as well-being, job satisfaction, etc. For example, one interesting idea may be to use tweets from charismatic leaders (who probably are too busy to fill out the VIA-IS) to predict their character strengths and thereby predict firm-level outcomes (e.g., the cognitive strengths might be more related to improvement of revenue, while the justice strength might be more related to sustainable behaviors). All these predictions could contribute to an array of new research interests.

Limitations and implications

Despite the strong face-validity of the language results, distinctive language insights for each individual strength need to be interpreted with caution because the influence of the

[5] We have uploaded the word and phrase clouds only controlled for age and gender to the Open Science Framework folder associated with this project (https://osf.io/m2dj8/).

other 23 strengths has been removed. For example, the language of *bravery* includes the connotation of being aggressive, likely because *kindness* and *love* are partialled out. This technique can provide a distillation of the unique qualities associated with any given strength but may provide a rather thin or caricatured view of each strength. As each of the VIA strengths contributes to generally positive life outcomes individually and on aggregate, the various strengths are often not only overlapping but mutually supportive and even constitutive of one another. Therefore, the VIA strengths can be viewed in a variety of different ways: as a sum total, as just a few factors, individually without controlling for the others, and individually while controlling for the influence of all of the others. We explore the last of these options because it had not been done previously and in order to provide a more granular and specific view of the linguistic correlates of the character strengths.

In addition, we acknowledge that our results are ultimately data- rather than theory-driven because we did not have a priori predictions about specific associations between character strengths and the linguistic markers. This approach is exploratory in the sense that it helps with hypothesis generation, in contrast to more traditional hypothesis testing often undertaken in psychology. The words presented in our clouds are the most highly-correlated, yet our interpretations are subjective. Readers are welcome to agree or disagree and future research is welcomed to test the hypotheses we generate.

Our participants are mainly from an internet source (Authentic Happiness Website) and were not purposefully recruited, possibly resulting in a biased recruitment of people who are interested in positive psychology or who are curious about themselves. As shown in the participants flow chart (see Supplementary Figure S1.), more than 3,000 volunteers gave invalid Twitter handles, which could indicate those who are honest were more likely to be included in our sample. These biases could affect the representativeness of the study. The lower amount of variance explained by the GPF compared to other studies (e.g., 41%, McGrath, 2015) might suggest greater homogeneity in our sample, which also could be seen from the characteristics of our sample (the majority of our participants were well-educated, English-speaking Americans). This means that the language features should be understood to describe our sample, not generalize widely. For this very reason we do not encourage using our findings to estimate character strengths in new samples without prior replication of the findings. Finally, in this study we predict inter-individual differences in the strengths, not intra-individual differences. Some applications of strengths focus on the “signature strengths,” i.e., the 3-7 most highly developed strengths; further research is needed before user-level signature strengths can be reliably predicted from Twitter language.

Conclusion

The current study demonstrates that social media can be used to further characterize and predict character strengths. The prediction results suggest that language-based assessments of character strengths may well serve as a cost-effective and scalable alternate measurement system. The consistent finding of a general “meta positivity” factor, in this study and in the literature, may suggest that research exploring differences across overlapping constructs (like character strengths) should adopt methods suitable to address this, such as partialling out the shared variance to foreground meaningful differences. The linguistic correlates associated with each character strength provide insights into the behavioral and social components of these morally valued traits, providing a rich set of hypotheses to explore in future research on character strengths.

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